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Review

Review of Methods for Diagnosing Faults in the Stators of BLDC Motors

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1. Introduction

Some desirable characteristics of permanent magnet motors make them very attractive candidates for various classes of industrial and commercial applications, such as robotic applications, motion control systems, aerospace systems and means of transport [1,2]. Permanent magnet motors can be classified according to where the magnets are placed: (1) on the stator, (2) on the rotor or (3) on both parts (see Figure 1). According to [3], motors with magnets in the stator can be classified into two groups: (1) the flux uncontrollable (FU) group and (2) the flux controllable (FC) group. The FU group can be classified into three types of *stator-PM machines*: doubly salient PM (DSPM) motors, flux-reversal PM (FRPM) motors and flux-switching PM (FSPM) motors. The FC group can be classified into flux-mnemonic permanent magnet motors and hybrid-excited permanent magnet motors.

Regarding the motors that have the magnets on the rotor, the most popular are the brushless direct current (BLDC) motors, permanent magnet synchronous (PMS) motors and permanent magnet stepper (PMST) motors, and they are known as *rotor-PM machines*. Since the operating principles of *rotor-PM machines* are essentially identical, the material presented in this review is applicable to this type of machine but with special emphasis on BLDC motors, due to the great interest of high-tech industries in their use in position and speed control applications, which for many years were commonly carried out by DC motors.

BLDC motors were developed to avoid the constant brush and commutator maintenance of DC motors, and it is thanks to this fact that BLDC motors have been gaining popularity in applications that require low-maintenance operations. This popularity can be verified by googling BLDC in `Google Trends`. The results of this search are shown in

Figure 2. In this figure, it can be noted that the number of searches has been increasing exponentially over the last few years.

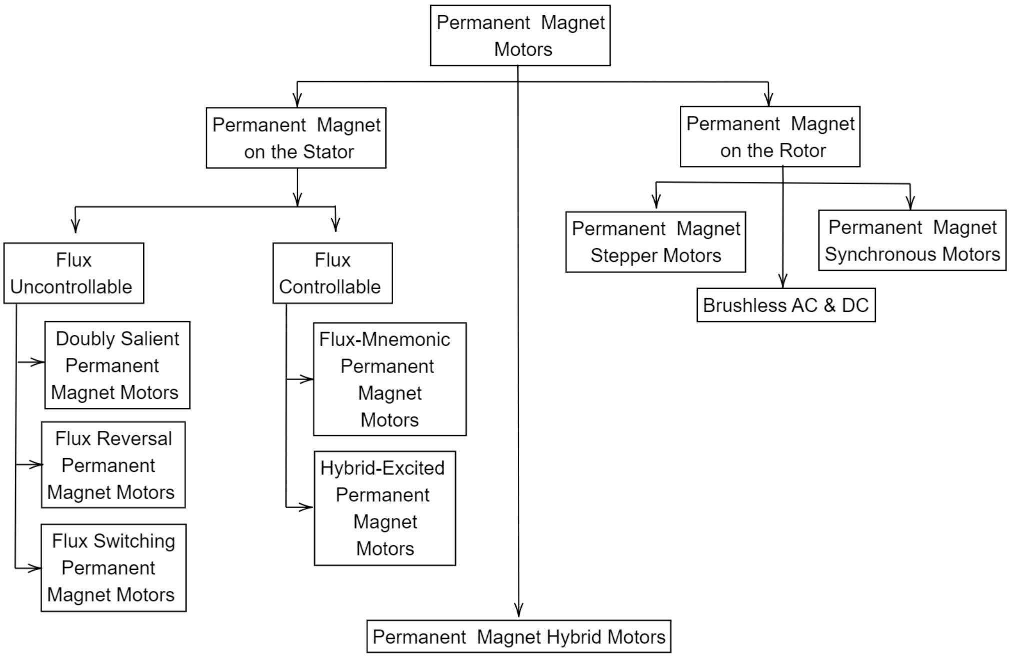

Figure 1. Classification of permanent magnet motors.

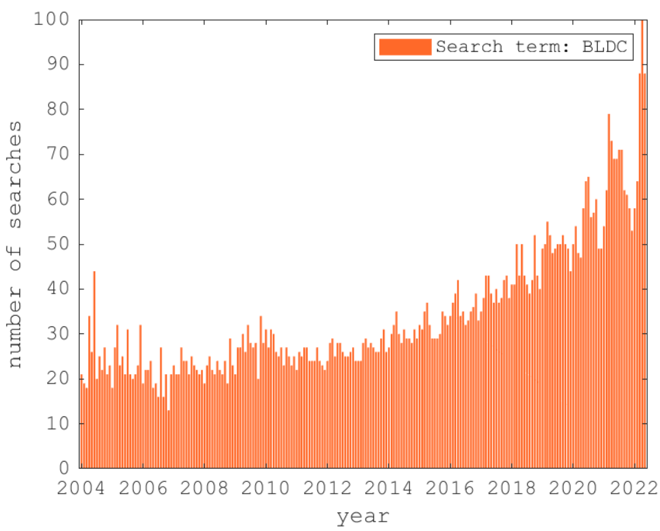

Figure 2. Trend of Google searches for the term BLDC.

The BLDC motor has electrical characteristics similar to those of a conventional DC motor but with the particularity that its reliability has been enhanced by the replacement of a mechanical commutation with an electronic one. The investigations that have been carried out with respect to these motors have allowed identifying the advantages that they present, among them being the following:

- A greater speed range due to non-dependence on the mechanical characteristics of the brushes;
- A better torque–speed characteristic due to the absence of friction produced by the brushes, which reduces the useful torque of the motor; in other words, a better capacity of heat dissipation that allows the generation of a higher torque;

- Better dynamic response due to the fact that the rotor has less inertia;
- Less noise due to the absence of discharges during the switching process;
- A smaller size, which widens its range of application.

Like most machines, BLDC motors are frequently used to work in harsh conditions, withstanding overloads and overheating. Thus, it is normal that faults occur over time. Winding-related faults are the most common faults in BLDC motors. Their main causes are high temperatures, loss of insulation, aging and contamination. If winding-related faults are detected at an early stage, it is possible to prevent catastrophic situations that can affect the environment and life. For this purpose, however, it is necessary to embed fault diagnosis systems in processes or applications that use BLDC motors.

According to [4,5], faults in BLDC motors can be classified as mechanical faults, electrical faults and magnetic faults, as shown Figure 3. According to [6–9], 30–40% of faults in BLDC motors occur in the stator. The main faults in the stator are shown in Figure 4, and they are insulation faults that provoke short circuits. A short circuit between turns is usually named an inter-turn fault. A short circuit between two coils bellowing to the same phase is called a coil-to-coil fault. A short circuit between two turns or two coils of different phases is called a phase-to-phase fault or inter-phase fault, respectively. A break in the wiring (or an abnormal operation that changes the resistance value to an extremely high value, ceasing the current flow) is an open-circuit fault [6].

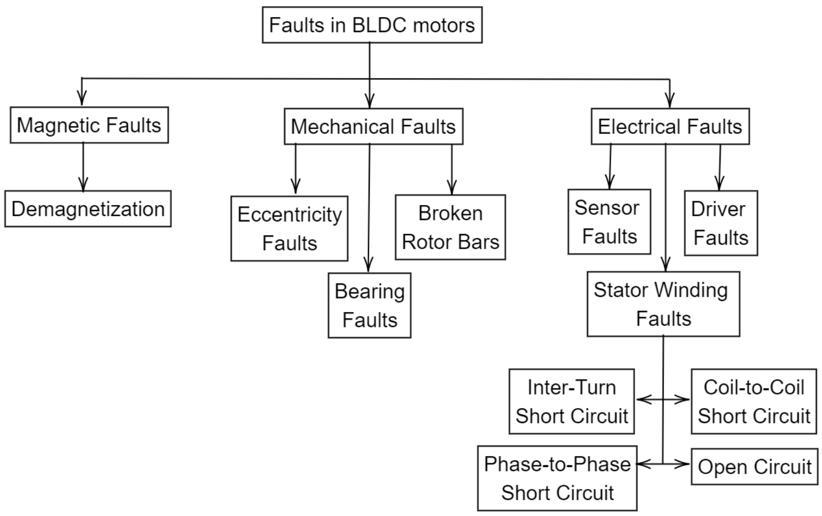

Figure 3. Classification of faults in a BLDC motor.

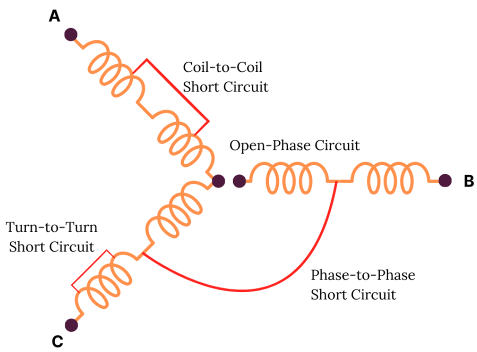

Figure 4. Common faults in the stator of a BLDC motor.

A review of health monitoring, fault diagnosis and failure prognosis techniques for brushless permanent magnet machines was presented in [4]. This review discusses in a general and brief way the different methods to diagnose and predict faults of various kinds in permanent magnet machines: electrical, mechanical and magnetic. To delve deeper into a topic that arouses more interest every day, the purpose of this work is to present a deep investigation of different methods and techniques for the diagnosis and detection of faults, specifically in the stator of BLDC motors. In particular, this review presents an analysis of the available diagnosis methods according to the type of stator fault, the method or technique used for the diagnosis (based on the signal, models or data), the diagnostic physical variables (current, position and frequency) and the context in which the methods are evaluated (in a simulation or in real time).

Section 2 presents a classification of the more common faults that happen in the stators of BLDC motors. Section 3 proposes a classification of the available methods for the diagnosis of stator faults, as well as a description of some of the most relevant methods. Finally, in Section 4, some conclusions are given.

2. Faults in the Stator

The identification of each stator fault can be accomplished through changes in the behavior of the machine quantities. These changes are known as *symptoms*. For example, if there is a significant reduction in phase current, a coil-to-coil fault is likely occurring. If there is a distinctly large cycle of Back-EMF, and the speed does not drop below the actual speed, the cause is likely to be a stator inter-turn failure. If the current is twice the healthy current, and the torque increases to three times the actual torque, a phase-to-phase fault may be occurring. Lastly, if zero current passes to any phase, then it is a winding fault or open circuit of such a phase [6,10].

2.1. Turn-to-Turn Short Circuit (Inter-Turn Fault)

The stator winding is the weakest part of BLDC motors. These windings are covered with insulating materials to prevent short circuits between adjacent windings. Organic materials used for insulation in electrical machines are subject to deterioration from a combination of thermal overload and cycling, voltage transients in the insulating materials, mechanical stress and contamination. If a fault occurs in the inter-turn stator windings, then shorted windings are produced, followed by extreme heat due to PM-induced current in the shorted windings. This type of fault is called an inter-turn fault (ITF) [8,11]. ITFs significantly affect the electromagnetic properties of a motor, such as variations in harmonic characteristics, inrush current, magnetic saturation, cross magnetization and back electromotive force (EMF). Furthermore, the propagation of ITFs can rapidly lead to total motor failure within a few seconds by causing excessive heat that is proportional to the square of the circulating current in the shorted turns [12,13]. The main causes of winding failures are excessive heat, loose insulation, aging due to operation and contamination, among others [5,14].

2.2. Phase Coil-to-Coil Fault (Coil-to-Coil Fault)

Compared with open-circuit faults, short circuits are more common faults that result from the failure of the insulation system, especially the insulation between turns. According to statistics, about 80% of electrical failures in the stator are due to weak insulation between turns. The build-up of ohmic heat can further deteriorate the surrounding insulation and subsequently develop other serious faults, such as coil-to-coil, phase-to-phase or phase-to-ground faults [15]. In addition, the great increase in currents, and especially the appearance of negative sequence currents during a coil-to-coil fault, are the causes of the appearance of another type of fault in the machine known as a demagnetization fault. Taking into account the above, research has been carried out involving implementing coil-to-coil fault diagnosis techniques and methods [10].

2.3. Fault between Phases (Phase-to-Phase Fault)

A short-circuit fault occurs when any two phases of a stator winding are shorted. For example, in a three-phase motor with Phase A, Phase B and Phase C, two of its phases are short-circuited, leading to a change in the performance of the machine. This results in a change in current at twice its nominal value for one phase, while in the other, it is less significant. This distinguishes it from coil-to-coil faults, where the overall change in phase current balances out and has no significant increase in current in either phase, although the sinusoidal nature is distorted. On the other hand, the back electromotive force also undergoes a significant change, and therefore the fluctuating magnitude goes beyond the nominal value [6]. Taking into account the above, research has been carried out for implementing phase-to-phase fault diagnosis techniques and methods [10].

2.4. Open-Circuit Fault of a Phase (Open-Circuit Fault)

An open-circuit winding fault occurs due to high inrush currents and sometimes due to high mechanical vibration opening the stator windings. Such a type of fault in any phase directly makes the current in that phase zero, since that phase is totally disconnected. Due to the open winding in one phase, two other phases are also affected, and the current increases. This type of fault is distinguished from the other faults mentioned above by a zero-current flow in any of the phases which are open stator windings. The back EMF of the machine decreases and fluctuates within the rated limits of the motor. There is not much of an increase in speed due to the depletion of the counter-electromotive force, but there is a non-stability, and the speed is no longer constant [6]. Taking into account the above, research has been carried out which implements open-circuit fault diagnosis techniques and methods.

A fault very similar to the open-circuit fault is the high-resistance connection (HRC) fault [16], which is the result of insulation aging, poor artistry and damaged surfaces due to corrosion. This type of fault makes the resistance increase and current decrease. When a motor runs with an HRC fault, the stator winding is asymmetric, which may lead to increased torque ripple, local overheating and additional loss, in addition to even more serious faults [17].

3. Classification of Methods for Diagnosing Faults in BLDC Motors

A fault is an impermissible deviation of at least one characteristic (feature) of a process from the usual and acceptable standard condition. A fault can be attributed to many causes, and sooner or later, it can lead to breakdowns if corrective measures are not taken [18]. The purpose of a fault diagnosis method is to determine the type, size and location of the most likely fault, as well as its detection time. The methods that have been used for diagnosing faults in BLDC motors can be classified into three categories: data-based, signal-based and process model-based methods [9,19].

3.1. Signal-Based Methods

A signal is a manifestation (visual, auditory, electrical, magnetic, etc.) of a physical phenomenon that can evolve in time or space. For practical purposes, signals provide information about the phenomenon or about the system (source) that is provoking it. To capture this information in the form of physical quantities (vibration, current and temperature), sensors are required. If a fault occurs in a system, it is very likely that some changes in its behavior will occur. These changes are symptoms that indicate that the system is not in a healthy condition. The usual symptoms are functions in the time domain, such as magnitudes, arithmetic or quadratic mean values, limit values, trends and statistical moments, or functions in frequency domain such as spectral power densities, frequency spectral lines and the cepstrum, among others [20].

The purpose of a fault diagnosis method based on a signal(s) is to extract information from one or more signals about a possible fault or set of faults occurring in a system. For extracting this information, the process illustrated in Figure 5 must be executed. The basic process only includes four tasks: acquisition, transformation, extraction and recognition. However, more than one signal is sometimes used for diagnosis. Therefore, an additional task is required: signal separation.

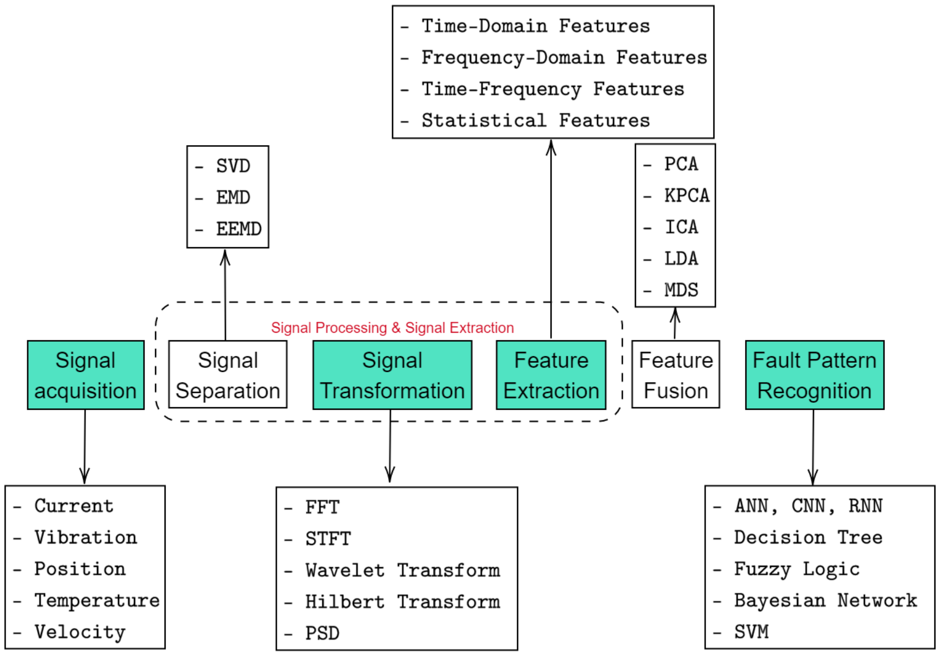

Figure 5. Process of fault diagnosis based on signals. The basic tasks of this process are signal acquisition, signal transformation, feature extraction and fault pattern recognition.

Many measured process signals show oscillations that are either harmonic or stochastic in nature, or both. If changes in these signals are related to faults in the actuators, process and sensors, fault detection methods based on signal models can be applied. Especially for machine vibration, the signals of position, velocity or acceleration allow one to detect, for example, imbalances or bearing failures (turbo machines), detonations (gasoline engines) and vibrations (metal grinding machines). However, the signals from many other sensors, such as the electric current, position, velocity, force, flow and pressure, also often contain oscillations with a variety of frequencies higher than the process dynamics [18].

Signal models can be divided into non-parametric models, such as frequency spectra or correlation functions, or parametric models, such as amplitudes for different frequencies or autoregressive–moving-average (ARMA) process-type models. Another way to classify signal-based methods is according to the nature of the signal: periodical, stochastic or non-stationary. Table 1 lists a classification of methods for the analysis of stationary periodic signals such as bandpass filtering or Fourier analysis for non-stationary periodic signals, such as wavelet transforms, and for stochastic signals, such as correlation functions, CUSUM and Kalman filters.

Table 1. Classification of methods based on signals according to the nature of the signal to be used for the diagnostic.

	Periodic Signals	Stochastic Signals	Non-Stationary Signals
Methods	Bandpass Filtering, Fourier Analysis, Parametric Spectral Estimation, Correlation Analysis	Correlation Analysis, CUSUM, Kalman Filter, ARMA	ARMA, STFT, Wavelet Analysis, Detrend Fluctuation Analysis

In [12], the authors used the harmonic analysis of the line currents to find the existence of a third harmonic that indicates the existence of an inter-turn fault. To evaluate the method, they used an FEM model to generate the current signals as well as an experimental set-up.

A recent method for diagnosing inter-turn faults was presented in [21]. The method employs the measured three-phase currents for the diagnostic. The method starts with the normalization of the measured currents, and then a modal current is calculated from these currents. Having the modal current, three different moving indices, namely the mean-based index (MBI), variance-based index (VBI) and energy-based index (EBI), are calculated in parallel to recognize the inter-turn fault condition. Application of these three indices enables the method to investigate the signal from three different aspects and increase the reliability and quickness of the fault diagnosis process. In addition, these indices are easy to calculate with simple mathematical operators. Hence, the method can be easily implemented online. To differentiate the healthy cases, such as load change, from faults, an auxiliary index is also computed. To justify the method with more details, the following four steps are taken into consideration.

In Table 2, some works that proposed signal based-methods for diagnosing inter-turn faults are listed together with the following particularities: the signal techniques used for the signal treatment, the measured variable(s) used for the diagnosis and the test environment in which the method was evaluated (simulated or experimental).

Table 2. Signal based-methods for diagnosing inter-turn faults. E = Experimental environment; S = simulation environment.

Reference	Main Methods	Measured Variables	S or E
[22]	PSD	Phase currents	S and E
[12]	HA	Line currents	S and E
[23–25]	HA, FEM	Phase currents, Back-EMF, electromagnetic torque, velocity	S
[26]	FFT	Phase currents	E
[27]	FFT, DWT	Phase currents	E
[21]	MBI, VBI, EBI	Phase currents	S and E
[10]	Bispectrum analysis	Phase currents	E
[28]	FFT	Phase currents	S and E

3.2. Model-Based Methods

Different methods for fault diagnosis using mathematical models have been developed for BLDC motors. These methods can be roughly classified into (1) methods without estimation error feedback and (2) methods with estimation error feedback. In the first method, the model is fed with the input information of the BLDC motor (voltages and torque). The response of the model (currents, angular displacement and angular velocity) is compared with the response of the BLDC motor. If there is a discrepancy between the responses, this is probably because there exists a fault or a set of faults. For obtaining good results with this type of method, it is necessary that the BLDC motor model is well-calibrated in healthy conditions. On the contrary, false alarms will appear. A drawback of this class is that a disturbance can be mistaken for a fault. Another drawback of methods without estimation error feedback is that they only serve to detect faults and not to locate or isolate them.

The methods with estimation feedback errors are more advantageous. The error between the model response and the BLDC motor response is injected into the model as an additional input and then multiplied by a gain that causes this error to move toward zero over time. These methods are (1) usefulness in detecting, locating and isolating faults, (2) usefulness for applications in real time and (3) robustness against disturbances. These methods are also known as observer based-methods, since a model with estimation error feedback is called a state observer. Usually, state observers are also called *virtual sensors* or *soft sensors*.

A state observer is an algorithmic tool that estimates variables such as the state variables, unknown inputs, disturbances, parameters and faults of a process (e.g., a BLDC motor). The parts of a state observer are (1) a mathematical model and (2) an error term (correction term) for ensuring the convergence of the algorithm. A state observer is fed with the available measurements of the process (inputs and outputs).

To derive a general structure of a state observer, let us consider the general structure of the continuous model of a system in a state-space representation, which is given as follows:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)), \\ y(t) &= h(x(t)), \end{aligned} \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state vector, $\dot{x}(t) \in \mathbb{R}^n$ is the state derivative vector, $u(t) \in \mathbb{R}^m$ is the external (exogenous) input vector or control signal, $y(t) \in \mathbb{R}^p$ represents the output vector (i.e., the measured states (variables) acquired by the sensors), $f \in \mathbb{R}^n$ represents the vector field and $h \in \mathbb{R}^p$ is the continuous output function. Since a state observer is the model of the system plus a correction (adaptation term), this can be expressed as follows:

$$\begin{aligned} \dot{\hat{x}}(t) &= \underbrace{f(\hat{x}(t), u(t))}_{\text{Model Copy}} + \underbrace{K(\hat{x}(t))(y(t) - \hat{y}(t))}_{\text{Correction Term}}, \\ \hat{y}(t) &= h(\hat{x}(t)), \end{aligned} \tag{2}$$

where $\hat{x}(t)$ and $\hat{y}(t)$ are the online estimations of $x(t)$ and $y(t)$, respectively, and $K(\hat{x}(t))$ is the gain of the observer. Thus, the design of the state observer consists of choosing an appropriate gain $K(\widehat{x}(t))$ so that the estimation error tends toward zero when $t \to \infty$ with the desired properties of time convergence and robustness. If the observation error $e(t)$ is defined as follows:

$$e(t) = x(t) - \hat{x}(t),$$

then the dynamics of the error observation can be derived from Equations (1) and (2) and expressed as

$$\dot{e}(t) = f(\hat{x}(t) + e(t), u(t)) - f(\hat{x}(t), u(t)) - K(\hat{x}(t))(h(\hat{x}(t) + e(t)) - h(\hat{x}(t))).$$

An observer connected to a BLDC motor has the structure of the block diagram shown in Figure 6. The inputs can be the the voltages or the torques. These inputs, or at least a subset of them, must be registered to be injected into the state observer. The state, which is the smallest possible subset of system variables that can represent the complete state of a system at any time, can be either the currents or the angular velocity. The measured outputs are the measurements provided by in situ sensors (position sensors or current sensors).

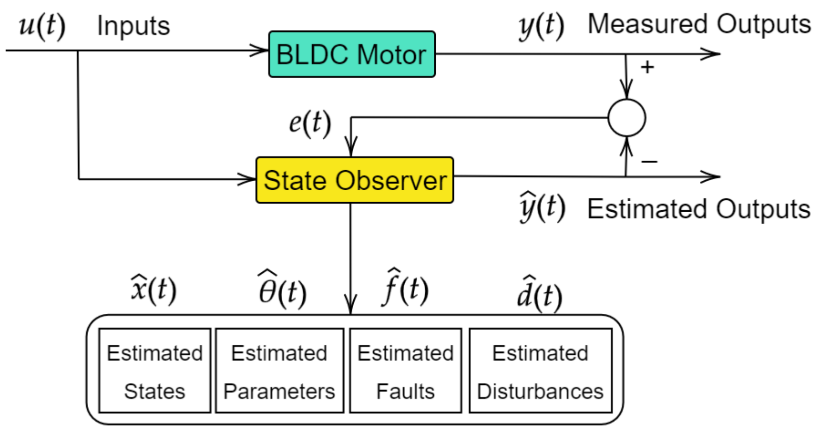

Figure 6. Architecture of a state observer.

The observer-based methods can be classified into three categories: (1) methods based on residual generation, (2) methods based on a bank of state observers and (3) methods based on parameter estimation. This classification is illustrated in Figure 7.

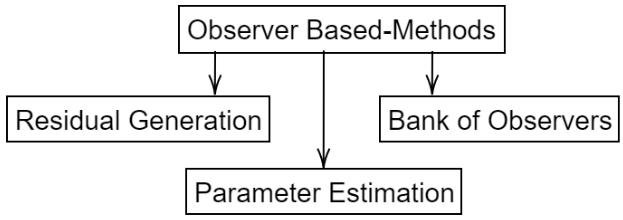

Figure 7. Methods based on state observers for diagnosing faults in the stators of BLDC motors.

Methods based on residual generation: A residual is an estimable quantity that can be used to warn if a fault occurs in a system. Usually, a residual is designed to be zero (or small enough in a realistic case where the process is subjected to noise and the model is uncertain) in the fault-free case and deviate significantly from zero when a fault occurs [29]. These methods comprise two stages: residual generation and residual evaluation. The easiest way to generate a residual is by estimating a variable (or set of variables) with the help of a state observer at the same time that this variable (or set of variables) is measured with hard sensors. Residuals can then be generated by subtracting the estimated variables from the measured variables such that

$$
\begin{aligned}
r_1(t) &= \quad y_1(t) - \hat{y}_1(t) \\
r_2(t) &= \quad y_2(t) - \hat{y}_2(t) \\
\vdots &= \qquad \vdots \\
r_n(t) &= \quad y_n(t) - \hat{y}_n(t)
\end{aligned}
$$

where r_i represents the residuals, y_i represents the measured outputs and $\hat{y}_i$ represents the estimated outputs $\forall i = 1, 2, \ldots, n$.

To evaluate a residual, it is necessary to establish some metric. The easiest way to evaluate a residual is by setting a threshold. If the residual exceeds this threshold, then there is a fault in the system; otherwise, there is not. A schema of residual based-methods is shown in Figure 8.

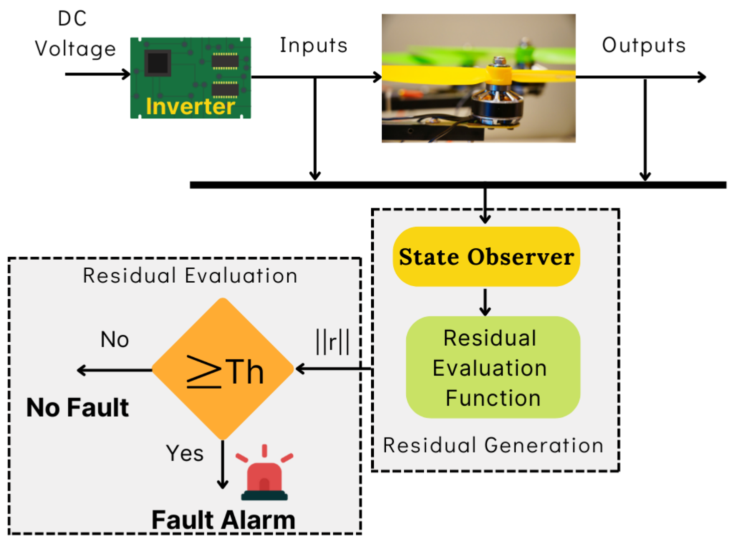

Figure 8. Usual architecture of methods based on residuals for diagnosing faults in the stators of BLDC motors.

In [30,31], the authors proposed fault diagnosis approaches based on a sliding mode observer that estimates the phase currents. The estimation error is used to generate residuals for the detection and location of a short-circuit fault in the stator winding turns.

Methods based on a bank of state observers: The architecture of these methods is illustrated in Figure 9. A bank of observers is made up of a set of state observers that work (estimate) in parallel. Each state observer is different from the other because each observer is constructed from a model involving a particular and different fault. For illustration purposes, let us consider a bank composed of three state observers. The first observer can be designed from a model with an open-circuit fault, and thus this observer will detect this kind of fault. The second observer can be constructed from a model with an inter-turn fault, and the third observer can be designed from a model with a phase-to-phase fault. The three observers receive the same information from the system (inputs and outputs), and the three observers compute an error estimation. The errors are evaluated by using suitable metrics to determine the smallest error. The fault will be the involved in the observer that produced the smallest error.

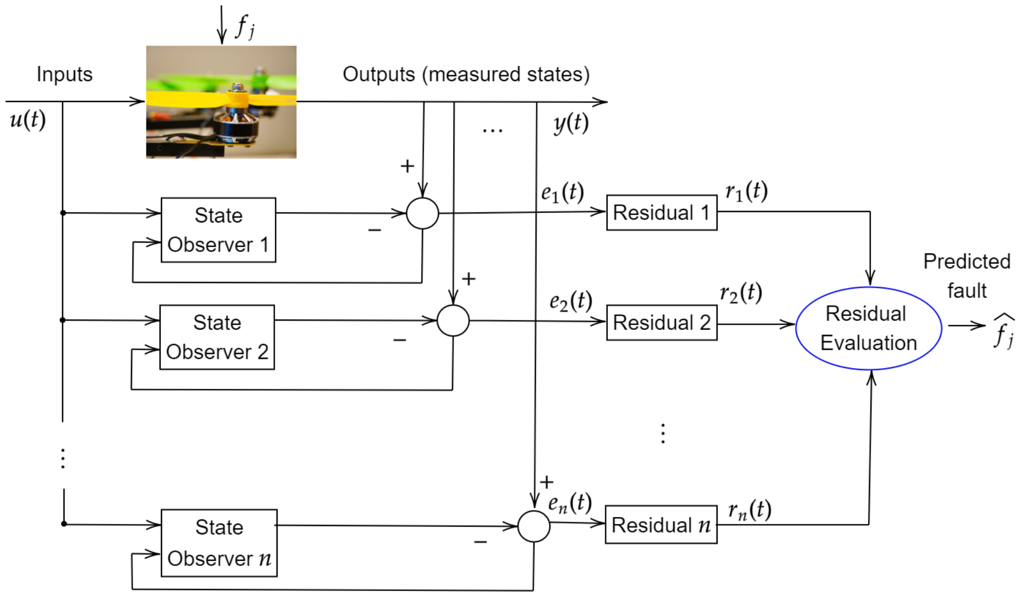

Figure 9. Bank of n observers, where $u(t)$ and $y(t)$ are the inputs and outputs (measured states) of the BLDC motor, respectively, $e_i(t)$ ($\forall i = 1, 2, \ldots, n$) is the error computed by the ith observer, $r_i(t)$ is the residual calculated from the error $e_i(t)$, f_j is the type of fault affecting the system and $\hat{f}_j$ is the estimated fault.

Methods based on the parameter estimation: When a fault happens in a BLDC motor, some parameters change. For example, damaged or broken bearings may augment the friction, or an increasing temperature in the stator may increase the phase resistance of all coils [32,33]. These parameter changes can be estimated by different algorithms, among them being the means of the state observers designed from mathematical models that involve the parameters of the BLDC motor. The architecture of these methods is illustrated in Figure 10. The fundamental idea of these methods is to directly estimate the parameters of the system by means of a state observer. Then, the estimated parameters are subtracted from the nominal parameters (i.e., from the values of the parameters under normal conditions). This is performed to calculate the error, which is evaluated using a predefined threshold. If the error exceeds this threshold, then there is a fault in the system. Depending on which parameter is evaluated, the type of fault can be determined.

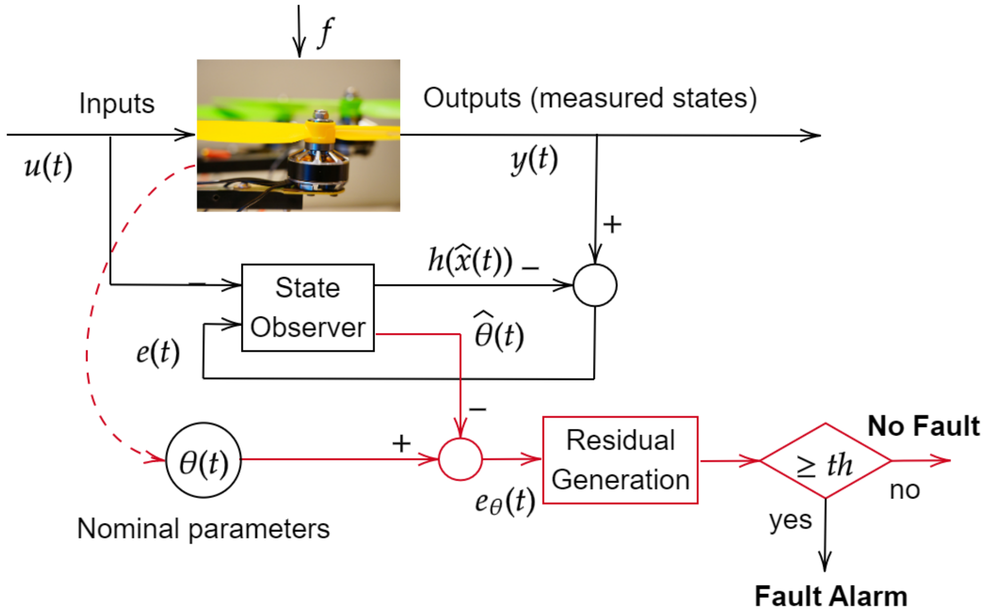

Figure 10. Methods based on parameters estimation, where $u(t)$ and $y(t)$ are the inputs and outputs (measured states) of the BLDC motor, respectively. $e(t)$ is the observation (estimation) error, $\theta(t)$ represents the parameters in nominal (normal) operation conditions, $h(\hat{x}(t))$ is the function output of the observer which is dependent on the estimated states, $\hat{\theta}$ represents the estimated states, $e_\theta(t)$ is the error between the nominal and estimated parameters and th is the threshold to surpass when there is a fault.

3.3. Data-Based Methods

Methods based on models are appropriate to be used when the dimension of the process (under diagnosis) is low and it can be modeled with low-order models. However, to diagnose faults in more complex systems, these methods are no longer recommended. An alternative to diagnose faults without using models is the use of data-based methods, which use information acquired from the process (under diagnosis). It can be said that these methods are the recent alternative for active supervision of systems too complex to have an explicit analytic model or signal symptoms of faulty behavior for.

The application of these diagnosis methods essentially consists of two stages: (1) training, in which the historical datasets are presented as a priori knowledge of the process under monitoring and transformed to a diagnostic system or algorithm, and (2) online running, in which the online measurement data are processed in the diagnostic system or by using the diagnostic algorithm for reliable fault detection and identification [20].

Data-based fault diagnosis methods can be categorized into two categories: supervised and unsupervised learning methods [34]. Unsupervised methods require the model to be initially developed using normal operation data. The faults are then detected as deviations from the normal behavior. Supervised methods require the training of a classifier on historical data which comprise both normal and faulty states. The trained model is then used for the detection of future faults.

In [35], Park et al. proposed a method that uses a database containing data on the phase currents and voltages of a BLDC motor under fault conditions. These data were obtained through numerical simulations using a model based on the FEM or using a WFT. From these data, the values of some input impedances under fault conditions were calculated. For diagnosis, the authors proposed comparing these fault impedances with the impedances obtained from the voltages and currents that were measured for diagnosis.

In [11], Hosseini et al. introduced a supervised data-based method to detect and classify faults in BLDC motors, namely stator inter-turn faults, rotor dynamic imbalance, rotor static imbalance and different combinations of these. The current signal of the BLDCM is used together with the motor torque and motor speed to achieve the classification of a broad range of faults. The fault features of the measured signals are extracted using a packet wavelet transform (PWT). These features, which include the energy, in the two modes of BLDCM operation, without load and with load, are used as input data for an ANN. The ANN weights are updated by particle swarm optimization (PSO) and a genetic algorithm (GA).

In [36], Borja et al. proposed a supervised learning method to classify different types of faults: bearing inner ring damage, inter-turn faults and holes in the rotor. The method uses k-nearest neighbors and a DWT for feature extraction.

Table 3 lists some of the most important contributions proposed for diagnosing inter-turn faults. Table 4 details some of the main characteristics of data-based methods.

Table 3. Data-based methods for diagnosing inter-turn faults.

Reference	Main Methods	Measured Variables	S or E
[11]	Wavelets, ANN, PSO, Gf	Motor torque, motor speed	S
[13]	Logic comparison, FEM	Back-EMF	S and E
[35]	WFT, FEA	Phase currents and voltages	S and E

Table 4. Comparison between supervised and unsupervised learning methods.

	Supervised Learning	Unsupervised Learning
Methods	Bayesian Network, Random Forest, Decision Tree, k-Nearest Neighbors, Fisher's Discriminant Analysis, Artificial Neural Networks, Support Vector Machine	Principal Component Analysis, Partial Least Square, Independent Component Analysis, Autoencoders
Features	(1) Require both input and output system data. (2) Require labeled data. (3) Predict the output. (4) Requiere supervision for training.	(1) Require only input system data. (2) Employ unlabeled data. (3) Find hidden patterns in data. (4) Do not requiere supervision for training.
Computational Complexity	(1) Very complex. (2) Require feedback to improve the accuracy of the prediction.	(1) Less complex. (2) No feedback is needed.
Learning	Offline learning (usually)	Online learning
End Goal	Predict an output. Develop a model to (1) predict new values or (2) understand existing relationship between input and output data.	Gain insight from data. Develop a model to (1) place observations from a dataset into a specific cluster or (2) create rules to identify associations between variables.
Subtypes	(1) Regression and (2) classification.	(1) Clstering and (2) association.
Performance	More accurate	Less accurate
Fault Classes	Known in advance	Not known in advance

3.4. Summary

Table 5 summarizes the advantages and disadvantages that various authors have found during application of the methods reviewed in this article. Table 6 summarizes the investigation of different techniques and methods for fault detection and diagnosis. The research task was carried out by collecting information from different documents, books, magazines, states of the art and reviews that allowed detailing characteristics about the type of fault to diagnose, the physical variables used to perform the diagnosis and if the method was executed in a simulation or online.

Table 5. Advantages and disadvantages of the main methods used for diagnosing stator faults in BLDC motors.

Method	Advantages	Disadvantages
Model-based	(1) Can be naturally integrated into a fault-tolerant control scheme. (2) Can be highly accurate. (3) Requires less data than data-based methods. (4) All phases of diagnosis (detection, isolation and identification) can be conceived using the same model. (5) Few hard sensors are required with respect to the other methods.	(1) They requiere well-calibrated models. (2) Real-life system physics is often too stochastic and complex to model. (3) Sample time (or sample frequency) is important.
Data-based	(1) Do not require some model based on the physics of the BLDC motor. (2) Therefore, they are suitable for applications where a model is not available. (3) Suitable for processes with many sensed variables (i.e., when a large quantity of data is available). (4) Sample time (or sample frequency) is not important.	(1) Diagnosis accuracy relies on data quantity and quality. (2) Historical data on the behavior of the BLDC throughout its active life is required. (3) A sizable quantity of sensors is required.
Signal-based	(1) Do not require some model based on the physics of the BLDC motor. (2) Historical information about the BLDC motor is not required.	(1) Risk of false alarms due to disturbances and changes in the BLDC operating conditions. (2) High-speed computing power for transforming signals in real time. (3) The accuracy of the diagnosis depends on the quality of the sensors that provide the signals. (4) Sample time (or sample frequency) is important.

Table 6. Description of diagnostic methods for stator faults in BLDC motors. For the implementation aspects, S = tested in simulation, E = experimentally tested, ON-L = it can work online (i.e., in real time) and OFF-L = it can work offline (i.e., it works with stored data).

Type of Fault	Method	Physical Variables	Implementation	Comp. Burden
Inter-Turn	FEM, KF, HA [12]	Current	S, E, ON-L	High
	Spectral methods, SVM methods [4]	Current	S, OFF-L	Medium
	WFT, FEM [8]	Inductance, torque, voltage	S, E, OFF-L	Medium
	WFT, FEM, [37]	Back-EMF, current	S, E, OFF-L	Medium
	WFT, FFT [35]	Impedance, current, voltage, coil resistance	S, E, OFF-L	Low

Table 6. *Cont.*

Type of Fault	Method	Physical Variables	Implementation	Comp. Burden
	Search coils, FEA [38]	Magnetic flux, voltage	S, E, OFF-L	High
	Hybrid analytical-numerical approach, ECC, FEMM [23]	Current	Co-S, OFF-L	High
	FFT, Park's phasor analysis [26]	Current	S, OFF-L	Medium
	ECC, MEC, numerical methods, hybrid models, IWFT [25]	Current	S, Co-S, E, OFF-L	High, medium (depending on the method)
	RUL, RNN, LSTM [39]	Voltage, torque, temperature, velocity, current	S, E, OFF-L	High
	Technique based on undulations in velocity [40]	Velocity	E, OFF-L	Low
	Self-encoding convolutional network model [41]	Phase currents	S, OFF-L (applicable online)	High
	LS, AE [42]	Resistivity, inductance, voltage	S, OFF-L (applicable online)	High
	Co-simulation multidomain technique, FEM [43]	Flux density, current, torque vibrations	Co-S, E, OFF-L	Medium
	SVW, FFT [44]	Currents	S, E, OFF-L	Medium
	FEI, FFT, WDT [27]	Current	S, E, OFF-L	High
	FEM [45]	Current, voltage, electromagnetic torque, temperature	S, E, OFF-L	Medium
	CNN [46]	Current	S, E, OFF-L	High
	Current observer [47]	Voltage, current, position, velocity	S, E, OFF-L	Low
	Sliding mode observer (SMO) [48]	Current, voltage	S, ON-L	Low

Table 6. *Cont.*

Type of Fault	Method	Physical Variables	Implementation	Comp. Burden
	SSAE, Siamese neural networks [49]	Current, impedance, torque	S, E, ON-L	High
	DTCRV [50]	Current	S, E, OFF-L	Low
	Wave packet transform [51]	Current, vibration signal of the stator	E, OFF-L	High
	TDF, WVD, CWD [52]	Current	S, E, OFFL	Medium
	KF [53]	Current, BEMF	S, E, OFF-L	Medium
	FFT [54]	Phase voltages	S, OFF-L	Medium
	KF [55]	Voltage (voltage residuals)	S, ON-L	High
	Spectral density estimator (PSD), Welch and Burg method [56]	Current	S, OFF-L	High
	PSD, MCSA [57]	Current	S, OFF-L	Medium
	Maxwel II. 2D, numerical methods, FEM [24]	eletromagnetic magnitude, phase currents, BFEM, Electromagnetic torque, velocity, magnetic flux density, flux linkage	Co-S, OFF-L	High
	Math models [58]	Current, torque	S, ON-L	Medium
	Arithmetic mean [59]	Current, position	S, OFF-L	Low
	FEM [60]	Electromagnetic torque	S, E, OFF-L	High
	KF [9]	Phase currents	S, ON-L	Low High
	FEM, EMD, WVD [61]	Current	S, OFF-L	High

Table 6. *Cont.*

Type of Fault	Method	Physical Variables	Implementation	Comp. Burden
Coil-to-coil	Fast Kurtogram autogram, MCSA [5]	Vibration, current	E, OFF-L	High
	MCSA [62]	Current	S, E, OFF-L	Medium
Phase-to-phase	FEM numerical methods [15]	BFEM, magnetic flux density, phase current	S, OFF-L	High
	FEM [63]	None	S, OFF-L	High
	Math model [64]	Self-inductions, mutual inductance, current	S, OFF-L	Medium
	DWT, ANN [65]	Voltage, current, sequence current negative	S, OFF-L	High
Open circuit	Wavelet transform, SVM, DWT, NCA [66]	Current	S, OFF-L	High
	FOC, current comparison method (voltage error) [67]	Current	S, E, OFF-L	Medium
	MPCC [68]	Current	S, E, OFF-L	Medium
	RMS [69]	Normalized current	S, OFF-L	Low
	DWT, NN [70]	Current, velocity	S, OFF-L	High
	Current residual [71]	Current, torque, voltage	S, ON-L	Low
	FFT [16]	Impedances	S, E, OFF-L	Low
	FEM and function wavelets [72]	Current	S, OFF-L	High

From the classification table, it can be noticed that most of the diagnostic methods designed for BLDC motors detect and locate inter-turn faults, and most of these methods are signal-based methods, which can be seen as a drawback if the application is subject to disturbances and noise, since signal-based methods are less robust than the other classes.

4. Conclusions

To carry out this work, information on diagnostic methods to detect faults in the stators of BLDC motors was collected. The purpose of this collection was to classify and analyze the information in order to convey to the reader a detailed summary of the current state of the subject. It is worth saying that all the methods presented, classified and discussed in this review are also useful for permanent magnet synchronous motors, since the only difference is that synchronous motors develop a sinusoidal back EMF instead of a trapezoidal back EMF. The collected information was structured in the following way: (1) a classification of the main methods to diagnose stator faults in BLDC motors, (2) a subclassification of each method class, (3) a table with the advantages and disadvantages of each method class, (4) a comparison between supervised and unsupervised learning methods, which are subclasses of data-based methods, and (5) a table that organized the methods according to the type of stator fault to be diagnosed, the physical variables used by each method, the environment in which the method was tested (simulated or experimental) and the computational burden of each method. It was observed that there are some data-based methods that use a lot of computational consumption for data processing, more computation time and more memory to store data, among other factors, which makes these methods not so appropriate for applications in which only a BLDC motor is involved, but they are recommended for industries that have a large number of motors. It was also noticed that most of the fault diagnosis methods use neural networks, wavelets and signal-based methods in general. However, these methods are not very robust to disturbances and unknown inputs, and thus speed and load variations can influence the fault diagnosis, leading to poor fault location or fault identification. Therefore, it is advisable to continue designing methods based on models, which are more robust, or methods that combine both approaches to take advantage of the benefits that both offer. Finally, most of the techniques use current and voltage as diagnostic variables and can only diagnose one or two faults. Therefore, it is advisable to design methods that incorporate more variables in order to detect more types of faults with the same algorithm.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Autoencoder
ANN	Artificial Neural Network
ARMA	Autoregressive–Moving-Average
CNN	Convolutional Neural Network
CWD	Choi–Williams Distribution
DC	Direct Current
DTCRV	Drive-Tolerant Current Residual Variance
DWT	Discrete Wavelet Transform
EBI	Energy-Based Index
ECC	Electrical Equivalent Circuit
EEMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Mode Decomposition
EMF	Electromotive Force

FEA	Finite Element Analysis
FEM	Finite Element Method
FEMM	Finite Element Method Magnetic
FEI	Fasor Espacial Instantaneo
FFT	Fast Fourier Transform
FOC	Field-Oriented Control
GA	Genetic Algorithm
HA	Harmonic Analysis
ICA	Independent Component Analysis
IWFT	Improved Winding Function Theory
KF	Kalman Filter
KPCA	Kernel Principal Component Analysis
LDA	Linear Discriminant Analysis
LS	Least Squares
LSTM	Long Short-Term Memory
MBI	Mean-Based Index
MDS	Multi-Dimensional Scaling
MEC	Magnetic Equivalent Circuit
MCSA	Motor Current Signature Analysis
MPCC	Model Predictive Current Control
NCS	Neighborhood Component Analysis
NN	Neural Network
PWT	Packet Wavelet Transform
PSD	Power Spectral Density
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
RMS	Root Mean Square
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
STFT	Short-Time Fourier Transform
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SMO	Sliding Mode Observer
SSAE	Stacked Sparse Autoencoders
TDF	Time–Frecuency Distribution
VBI	Variance-Based Index
WFT	Winding Function Theory
WVD	Wigner–Ville Distribution

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